Finite-Length Equalization Over Multi-Input Multi-Output Channels
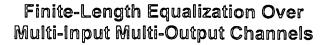
Related Application:

5   This application claims priority from Provisional application No. 60/158,714, filed on October 8, 1999. This application is also related to a Provisional application No. 60/158,713, also filed on October 8, 1999.

Background of the Invention:

10   In multi-user communication over linear, dispersive, and noisy channels, the received signal is composed of the sum of several transmitted signals corrupted by inter-symbol interference, inter-user interference, and noise. Examples include TDMA digital cellular systems with multiple transmit/receive antennas, wide-band asynchronous CDMA systems, where inter-user interference is also known as

15   multiple access interference, wide-band transmission over digital subscriber lines (DSL) where inter-user interference takes the form of near-end and far-end crosstalk between adjacent twisted pairs, and in high-density digital magnetic recording where inter-user interference is due to interference from adjacent tracks.

Multi-user detection techniques for multi-input multi-output (MIMO) systems

20   have been shown to offer significant performance advantages over single user detection techniques that treat inter-user interference as additive colored noise and lumps its effects with thermal noise. Recently, it has been shown that the presence of inter-symbol interference in these MIMO systems could enhance overall system capacity, provided that effective multi-user detection techniques are

25   employed.

The optimum maximum likelihood sequence estimation (MLSE) receiver for MIMO channels was developed by S. Verdu, "Minimum Probability of Error for Asynchronous Gaussian Multiple Access Channels," *IEEE Transactions on Information Theory*, January 1986, pp. 85-96. However, its exponential complexity

30   increases with the number of users, and channel memory makes its implementation costly for multi-user detection on severe-inter-symbol interference channels.

Two alternative transceiver structures have been recently proposed for MIMO dispersive channels as well. These structures, which are widely used in practice for single-input single-output dispersive channels, are the Discrete Multitone and minimum-mean-square-error decision feedback equalizer (MMSE-

5   DFE). In the latter category, this includes A. Duel-Hallen "Equalizers for Multiple Input Multiple Output Channels and PAN Systems with Cyclostationary Input Sequences," *IEEE Journal on Selected Areas on Communications*, April 1992, pp. 630-639; A. Duel-Hallen "A Family of Multiuser Decision-Feedback Detectors for Asynchronous Code Division Multiple Access Channels," *IEEE Transactions on*

10   *Communications*, Feb/Mar/April 1995, pp. 421-434; J. Yang et an "Joint Transmitter and Receiver Optimization for Multiple Input Multiple Output Systems with Decision Feedback," *IEEE Transactions on Information Theory*, Sep. 1994, pp. 1334-1347; and J. Yang et al "On Joint Transmitter and Receiver Optimization for Multiple Input Multiple Output (MIMO) Transmission Systems," *IEEE*

15   *Transactions on Communications*, Dec. 1994, pp. 3221-3231. Alas, the prior art does not offer a practical MIMO MMSE-DFE receiver with feedforward and feedback FIR filters whose coefficients can be computed in a single computation (i.e., non-iteratively) in real-time under various MIMO detection scenarios.

Summary

20   An advance in the art is realized with receiver having a multiple number of receiving antennas that feed a MIMO feedforward filter that is constructed from FIR filters with coefficients that are computed based on environment parameters that are designer-specified. Signals that are derived from a multiple-output

25   feedback filter structure are subtracted from the signals from the multiple outputs of the feedforward filter structure, and the resulting difference signals are applied to a decision circuit. Given a transmission channel that is modeled as a set of FIR filters with memory v, a matrix W is computed for a feedforward filter that results in an effective transmission channel B with memory N_b, where $N_b \leq v$, where B is

30   optimized so that $B_{opt} = \text{argmin}_B \, trace(R_{ee})$ subject to selected constraints; R_{ee} being the error autocorrelation function. The feedback filter is modeled by

$\left[\mathbf{I}_{n_i} \quad \mathbf{0}_{n_i \times n_i N_b} \right] - \mathbf{B}^*$, where n_i is the number of outputs in the feedforward filter, as well as the number of outputs in the feedback filter.

The coefficients of feedforward and the feedback filters, which are sensitive to a variety of constraints that can be specified by the designer, are computed by a

5 processor in a non-iterative manner, only as often as it is expected for the channel characteristics to change.

Brief Description of the Drawing

FIG. 1 shows the major elements of a receiver in accord with the principles

10 disclosed herein;

FIG. 2 presents the structure of elements 23 and 26;

FIG. 3 is a flowchart describing one method carried out by processor 22;

and

FIG. 4 is a flowchart describing another method carried out by processor

15 22.

Detailed Description

FIG. 1 depicts the general case of an arrangement with n_i transmitting antennas 11-1, 11-2, ... 11-n_q, that output signals (e.g., space-time encoded

20 signals) to a transmission channel, and n_o receiving antennas 21-1, 21-2, ... 21-n_o. Each transmitting antenna p outputs a complex-valued signal x_p, the signals of the n_q antennas pass through a noisy transmission channel, and the n_o receiving antennas capture the signals that passed through the transmission channel. The received signals are oversampled by a factor of l in element 20 and applied to

25 feedforward W filters 23. Thus, the sampling clock at the output of element 20 is of period $T_s = T/l$, where T is the inter-symbol period at the transmitting antennas. The transmission channel's characterization is also referenced to T_s.

Filter bank 23 delivers an n_i plurality of output signals (n_i can equal n_q for example) from which feedback signals are subtracted in circuit 24 and applied to

30 decision circuits 25 (comprising conventional slicers). The outputs of decision circuits 25 are applied to feedback filters 26, which develop the feedback signals.

Processor 22 develops the filter coefficients for the filters within elements 23 and 26 and installs the coefficients in the filters within these elements, as disclosed in detail below.

In the illustrative embodiment disclosed herein, the received signal is expressed by

$$y_k^{(j)} = \sum_{i=1}^{N} \sum_{m=0}^{v^{(i,j)}} h_m^{(i,j)} x_{k-m}^{(i)} + n_k^{(j)} , \qquad (1)$$

where $y_k^{(j)}$ is the signal at time k at the jth receiving antenna, $h_m^{(i,j)}$ is the mth coefficient (tap) in the channel impulse response between the ith transmitting antenna and the jth receiving antenna, and $n^{(j)}$ is the noise vector at the jth receiving antenna. The memory of this path (i.e., the largest value of m for which $h_m^{(i,j)}$ is not zero) is denoted by $v^{(i,j)}$.

It may be noted that it not unreasonable to assume, that the memory of the transmission channel is the same for all i,j links ($n_i \times n_o$ such links), in which case $v^{(i,j)} = v$. Alternatively, the $v^{(i,j)}$ limit in equation (1) can be set to that v which corresponds to maximum length of all of the $n_i \times n_o$ channel input responses, i.e., $v = \max_{i,j} v^{(i,j)}$. It may also be noted that all of the variables in equation (1) are actually $l \times 1$ column vectors, corresponding to the l time samples per symbol in the oversampled FIG. 1 arrangement.

By grouping the received samples from all n_0 antennas at symbol time k into an $n_o l \times 1$ column vector y_k, one can relate y_k to the corresponding $n_i \times 1$ (column) vector of input samples as follows

$$y_k = \sum_{m=0}^{v} H_m x_{k-m} + n_k , \qquad (2)$$

where H_m is the MIMO channel coefficients matrix of size $n_o l \times n_i$, x_{k-m} is a size $n_i \times 1$ input (column) vector, and n_k is a size $n_o l \times 1$ vector.

Over a block of N_f symbol periods, equation (2) can be expressed in matrix notation as follows:

$$\begin{bmatrix} y_{k+N_f-1} \\ y_{k+N_f-2} \\ \vdots \\ y_k \end{bmatrix} = \begin{bmatrix} H_0 & H_1 & \cdots & H_v & 0 & \cdots & 0 \\ 0 & H_0 & H_1 & \cdots & H_v & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & H_0 & H_1 & \cdots & H_v \end{bmatrix} \begin{bmatrix} x_{k+N_f-1} \\ x_{k+N_f-2} \\ \vdots \\ x_{k-v} \end{bmatrix} + \begin{bmatrix} n_{k+N_f-1} \\ n_{k+N_f-2} \\ \vdots \\ n_k \end{bmatrix} \qquad (3)$$

or, more compactly,

$$y_{k+N_f-1:k} = Hx_{k+N_f-1:k-v} + n_{k+N_f-1:k} . \qquad (4)$$

The subscripts in equation (4) indicate a range. For example $k + N_f - 1 : k$ means

the range from $k + N_f - 1$ to k, inclusively.

It is useful to define the following correlation matrices:

$$R_{xy} \equiv E[x_{k+N_f-1:k-v} y^*_{k+N_f-1:k}] = R_{xx} H^* \qquad (5)$$

$$R_{yy} \equiv E[y_{k+N_f-1:k} y^*_{k+N_f-1:k}] = H R_{xx} H^* + R_{nn} , \qquad (6)$$

$$R_{xx} \equiv E[x_{k+N_f-1:k-v} x^*_{k+N_f-1:k-v}] \text{ and} \qquad (7)$$

$$R_{nn} \equiv E[n_{k+N_f-1:k} n^*_{k+N_f-1:k}] , \qquad (8)$$

and it is assumed that these correlation matrices do not change significantly in time or, at least, do not change significantly over a time interval that corresponds to a TDMA burst (assumed to be much shorter than the channel coherence time), which is much longer than the length of the FIR filters in element 23 (in symbol periods denoted by N$_f$). Accordingly, a re-computation within processor 22 of the above matrices, and the other parameters disclosed herein, leading to the computation of the various filter coefficients, need not take place more often than once every TDMA burst. Once H, R_{xx} and R_{nn} are ascertained (through the conventional use of training sequences), R_{xy} and R_{yy} are computed by $R_{xx} H^*$ and $H R_{xx} H^* + R_{nn}$, respectively.

In accordance with the principles disclosed herein, element 23 comprises a collection of FIR filters that are interconnected as shown in FIG. 2, and the impulse response coefficients of element 23 can be expressed by $W^* \equiv [W_0^* \ W_1^* \cdots W_{N_f-1}^*]$, each having N_f matrix taps W_i, of size $(I_0 n \times n_i)$. That is, W_i has the form:

$$W_i = \begin{bmatrix} w_i^{(1,1)} & \cdots & w_i^{(1,n_i)} \\ \vdots & \cdots & \vdots \\ w_i^{(n_o,1)} & \cdots & w_i^{(n_o,n_i)} \end{bmatrix} \qquad (9)$$

where each entry in $W_j^{(p,q)}$ is an $l \times 1$ vector corresponding to the l output samples per symbol. Stated in other words, the matrix W_0 specifies the 0th tap of the set of filters within element 23, the matrix W_1 specifies the 1st tap of the set of filters within element 23, etc.

Also in accordance with the principles disclosed herein, element 26 comprises a collection of FIR filters that also are interconnected as shown in FIG. 2, and the impulse response coefficients of element 26 is chosen to be equal to

$$\begin{bmatrix} I_{n_i} & 0_{n_i \times n_i N_b} \end{bmatrix} - B^* \equiv \begin{bmatrix} (I_{n_i} - B_0^*) & B_1^* & \cdots & B_{N_b}^* \end{bmatrix}, \qquad (10)$$

where B^* is expressed by $B^* \equiv \begin{bmatrix} B_0^* & B_1^* \cdots B_{N_b}^* \end{bmatrix}$, with $(N_b + 1)$ matrix taps B_i, each of size $n_i \times n_i$. That is, B_i has the form:

$$B_i = \begin{bmatrix} b_i^{(1,1)} & \cdots & b_i^{(1,n_i)} \\ \vdots & \cdots & \vdots \\ b_i^{(n_i,1)} & \cdots & b_i^{(n_i,n_i)} \end{bmatrix}. \qquad (11)$$

Stated in other words, B_0 specifies the 0th tap of the set of filters within element 26, the matrix B_1 specifies the 1st tap of the set of filters within element 26, etc.

Defining $\tilde{B}^* \equiv [0_{n_i \times n_i \Delta_b} \ B^*]$, where $\tilde{B}^*$ is a matrix of size $n_i \times n_i(N_f + v)$, the value of N_b is related to the decision delay by the equality $(\Delta + N_b + 1) = (N_f + v)$.

The error vector at time k is given by

$$E_k = \tilde{B}^* x_{k+N_f-1:k-v} - W^* y_{k+N_f-1:k}. \qquad (12)$$

Therefore, the $n_i \times n_i$ error auto-correlation matrix is

$$R_{ee} \equiv E[\tilde{E}_k^* E_k]$$
$$= \tilde{B}^* R_{xx} \tilde{B} - \tilde{B}^* R_{xy} W - W^* R_{yx} \tilde{B} + W^* R_{yy} W$$
$$= \tilde{B}^* (R_{xx} - R_{xy} R_{yy}^{-1} R_{yx}) \tilde{B} + (W^* - \tilde{B}^* R_{xy} R_{yy}^{-1}) R_{yy} (W^* - \tilde{B}^* R_{xy} R_{yy}^{-1}) \quad (13)$$
$$= \tilde{B}^* R^{\perp} \tilde{B} + G^* R_{yy} G$$

Using the *Orthogonality Principle*, which states that $E[E_k y_{k+N_f-1:k}^*] = 0$, it can

be shown that the optimum matrix feedforward and feedback filters are related by

$$W_{opt}^* = \tilde{B}_{opt}^* R_{xy} R_{yy}^{-1}$$
$$= \tilde{B}_{opt}^* R_{xx} H^* (H R_{xx} H^* + R_{nn})^{-1} \quad (14)$$
$$= \tilde{B}_{opt}^* (R_{xx}^{-1} + H^* R_{nn}^{-1} H)^{-1} H^* R_{nn}^{-1},$$

5 and the $n_i \times n_i$ auto-correlation matrix R_{ee} is

$$R_{ee} \equiv E[E_k E_k^*]$$
$$= \tilde{B}^* (R_{xx} - R_{xy} R_{yy}^{-1} R_{yx}) \tilde{B}$$
$$= \tilde{B}^* R^{\perp} \tilde{B} \quad (15)$$
$$= \tilde{B}^* (R_{xx} - R_{xx} H^* (H R_{xx} H^* + R_{nn})^{-1} H R_{xx}) \tilde{B}$$
$$= \tilde{B}^* (R_{xx}^{-1} + H^* R_{nn}^{-1} H)^{-1} \tilde{B}.$$

R_{ee} can also be expressed as $R_{ee} = \tilde{B}^* R^{-1} \tilde{B}$, where $R = R_{xx}^{-1} + H^* R_{nn}^{-1} H$.

It remains to optimize values for the B matrix and the W matrix such that, in

response to specified conditions, the *trace* (or determinant) of R_{ee} is minimized.

10 The following discloses three approaches to such optimization.

Scenario 1

In this scenario, it is chosen to process only previous receiver decisions.

These decisions relate to different users that concurrently have transmitted

information that has been captured by antennas 21 and detected in circuit 25.

15 That means that feedback element 26 uses only delayed information and that the

0th order coefficients of the filters within element 26 have the value 0. Therefore,

in light of the definition expressed in equation (10), this scenario imposes the

constraint of $B_0 = I_{n_i}$.

To determine the optimum matrix feedback filter coefficients under this

20 constraint, the following optimization problem needs to be solved:

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$$min_{\tilde{B}} R_{ee} = min_{\tilde{B}} \tilde{B}^* R^{-1} \tilde{B}, \text{ subject to } \tilde{B}^* \Phi = C^*, \tag{16}$$

where

$$\Phi \equiv \begin{bmatrix} I_{n_i} & 0 & \cdots & 0 \\ 0 & I_{n_i} & \vdots & \vdots \\ \vdots & 0 & \ddots & I_{n_i} \\ 0 & \cdots & \cdots & 0 \end{bmatrix} \text{ and } C^* = \begin{bmatrix} 0_{n_i \times n_i \Delta} & I_{n_i} \end{bmatrix} \tag{17}$$

It can be shown that the solution to the above is given by

$$\tilde{B}_{opt} = R\Phi(\Phi^* R\Phi)^{-1} C, \tag{18}$$

resulting in the error signal

$$R_{ee,min} = C^*(\Phi^* R\Phi)^{-1} C. \tag{19}$$

If we define the partitioning

$$R \equiv \begin{bmatrix} R_{11} & R_{12} \\ R_{12}^* & R_{22} \end{bmatrix}, \tag{20}$$

where R_{11} is of size $n_i(\Delta+1) \times n_i(\Delta+1)$, then

$$\tilde{B}_{opt} = \begin{bmatrix} R_{11} \\ R_{12}^* \end{bmatrix} R_{11}^{-1} C = \begin{bmatrix} I_{n_i(\Delta+1)} \\ R_{12}^* R_{11}^{-1} \end{bmatrix} C \tag{21}$$

and

$$R_{ee,min} = C^* R_{11}^{-1} C, \tag{22}$$

where the delay parameter Δ is adjusted to minimize the *trace* (or determinant) of $R_{ee,min}$. Once $\tilde{B}_{opt}$ is known, equation (14) is applied to develop W_{opt}^*.

FIG. 3 presents a flowchart for carrying out the method of determining the filter coefficients that processor 22 computes pursuant to scenario 1. Step 100 develops an estimate of the MIMO channel between the input points and the output point of the actual transmission channel. This is accomplished in a conventional manner through the use of training sequences. The estimate of the MIMO channel can be chosen to be limited to a given memory length, v, or can be allowed to include as much memory as necessary to reach a selected estimate error level. That, in turn, depends on the environment and is basically equal to the delay spread divided by T_s.

Following step 100, step 110 determines the matrices, R_{nn}, R_{xx}, R_{xy}, and R_{yy}. The matrix R_{nn} is computed by first computing $n = y - Hx$ and then computing the expected value $E[n^{\ast}n]$ -- see equation (8) above. The matrix R_{xx} is computed from the known training sequences -- see equation (7) above -- (or is pre-computed and installed in processor 22). In may be noted that for uncorrelated inputs, $R_{xx}=I$. The matrices R_{xy} and R_{yy} are computed from the known training sequences and the received signal or directly from H and R_{nn}-- see equations (5) and (6) above.

Following step 110, step 120 computes $R = R_{xx}^{-1} - H^{\ast}R_{nn}^{-1}H$, and the partition components, R_{11}, R_{12}, and R_{22}, as per equation (20). Following step 120, step 130 computes $R_{ee,min}$ from equation (22) and adjusts Δ to minimize the *trace* (or determinant) of $R_{ee,min}$, computes $\tilde{B}_{opt}$ from equation (21), and from $\tilde{B}_{opt}$ determines the coefficients of the $n_i \times n_i$ filters of element 26, pursuant to equation (10). Step 140 computes $W_{opt}^{\ast}$ from equation (14), and finally, step 150 installs the coefficients developed in step 130 into the filters of element 26 and the coefficients developed in step 140 into the filters of element 23.

A second approach for computing $\tilde{B}_{opt}$ utilizes the *block* Cholesky factorization (which is a technique that is well known in the art):

$$R \equiv R_{xx}^{-1} + H^{\ast}R_{nn}^{-1}H$$
$$= \begin{bmatrix} L_1 & 0 \\ L_2 & L_3 \end{bmatrix}\begin{bmatrix} D_1 & 0 \\ 0 & D_2 \end{bmatrix}\begin{bmatrix} L_1^{\ast} & L_2^{\ast} \\ 0 & L_3^{\ast} \end{bmatrix} \qquad (22)$$
$$\equiv LDL^{\ast},$$

where L_1 is of size $n_i(\Delta+1) \times n_i(\Delta+1)$. Using the result in equations (18) and (19) yields

$$\tilde{B}_{opt} = \begin{bmatrix} I_{n_i(\Delta+1)} \\ L_2L_1^{-1} \end{bmatrix}C = \begin{bmatrix} I_{n_i} \\ L_2L_1^{-1}C \end{bmatrix} \qquad (23)$$
$$= L\left[e_{n_i\Delta_{opt}} \cdots e_{n_i(\Delta_{opt}+1)-1} \right]$$

and

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$$R_{ee,min} = C^{\cdot}D_1^{-1}C$$
$$= diag(d_{n_i\Delta_{opt}}^{-1}, \cdots, d_{n_i(\Delta_{opt}+1)-1}^{-1}), \tag{24}$$

where the index Δ_{opt} is chosen (as before) to minimize the trace and determinant

of $R_{ee,min}$. Using equation (23), equation (14) can be expressed as follows

$$W_{opt}^{\cdot} = \tilde{B}_{opt}^{\cdot}R_{xx}H^{\cdot}(HR_{xx}H^{\cdot} + R_{nn})^{-1}$$
$$= \tilde{B}_{opt}^{\cdot}(R_{xx}^{-1} + H^{\cdot}R_{nn}^{-1}H)^{-1}H^{\cdot}R_{nn}^{-1} \tag{25}$$
$$= \begin{bmatrix} d_{n_i\Delta_{opt}}^{-1}e_{n_i\Delta_{opt}}^{\cdot} \\ \vdots \\ d_{n_i(\Delta_{opt}+1)-1}^{-1}e_{n_i(\Delta_{opt}+1)-1}^{\cdot} \end{bmatrix} L^{-1}H^{*}R_{nn}^{-1}$$

Yet a third approach for computing $\tilde{B}_{opt}$ and $R_{ee,min}$ defines $\tilde{B}^{\cdot} = \begin{bmatrix} C^{\cdot} & \tilde{B}^{\cdot} \end{bmatrix}$

and partitions $R^{\perp}$ into as $\begin{bmatrix} R_{11}^{\perp} & R_{12}^{\perp} \\ R_{12}^{\perp^{\cdot}} & R_{22}^{\perp} \end{bmatrix}$, where $R_{11}^{\perp}$ is of size $n_i(\Delta+1) \times n_i(\Delta+1)$, to

yield

$$R_{ee} = \tilde{B}^{\cdot}R^{\perp}\tilde{B}$$
$$\equiv \begin{bmatrix} C^{\cdot} & \tilde{B}^{\cdot} \end{bmatrix} \begin{bmatrix} R_{11}^{\perp} & R_{12}^{\perp} \\ R_{12}^{\perp^{\cdot}} & R_{22}^{\perp} \end{bmatrix} \begin{bmatrix} C \\ B \end{bmatrix}$$
$$\equiv \begin{bmatrix} I_{n_i} & \bar{B}^{\cdot} \end{bmatrix} \begin{bmatrix} \bar{R}_{11}^{\perp} & \bar{R}_{12}^{\perp} \\ \bar{R}_{12}^{\perp^{\cdot}} & \bar{R}_{22}^{\perp} \end{bmatrix} \begin{bmatrix} I_{n_i} \\ \bar{B} \end{bmatrix} \tag{26}$$
$$= (\bar{R}_{11}^{\perp} - \bar{R}_{12}^{\perp}(\bar{R}_{22}^{\perp})^{-1}\bar{R}_{12}^{\perp^{\cdot}}) + (\bar{B}^{\cdot} + \bar{R}_{12}^{\perp}(\bar{R}_{22}^{\perp})^{-1})R_{22}^{\perp}(\bar{B}^{\cdot} + \bar{R}_{12}^{\perp}(\bar{R}_{22}^{\perp})^{-1})^{\cdot},$$

where $\bar{R}_{11}^{\perp} \equiv C^{\cdot}R_{11}^{\perp}C$ and $\bar{R}_{12}^{\perp} = C^{\cdot}R_{12}^{\perp}$. Therefore,

$$B_{opt} = -\bar{R}_{12}^{\perp}(R_{22}^{\perp})^{-1}$$
$$W_{opt}^{\cdot} = [0_{n_i \times n_i\Delta} \quad I_{n_i} \quad -\bar{R}_{12}^{\perp}(R_{22}^{\perp})^{-1}](R_{xx}H^{*}(HR_{xx}H^{*} + R_{nn})^{-1} \tag{27}$$
$$R_{ee,min} = \bar{R}_{11}^{\perp} - \bar{R}_{12}^{\perp}(R_{22}^{\perp})^{-1}\bar{R}_{12}^{\perp^{*}} \tag{28}$$

Scenario 2

In this scenario it is assumed that users whose signals are received by the

FIG. 1 receiver are ordered so that lower-indexed users are detected first, and

current decisions from lower-indexed users are used by higher-indexed users in

making their decisions, i.e., B_0 is a lower-triangular matrix. The general results of

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equations (21) and (22) can be applied by setting $C^* = \begin{bmatrix} 0_{n_i \times n_i \Delta} & B_0^* \end{bmatrix}$ where B_0 is an $n_i \times n_i$ monic lower-triangular matrix whose entries are optimized to minimize $trace(R_{ee,min})$. To this end, a partitioning can be defined where

$$R_{11}^{-1} \equiv \begin{bmatrix} R_1 & R_2 \\ R_2^* & R_3 \end{bmatrix}, \tag{29}$$

5   R_{11} being the term corresponding to R_{11} of equation (20), with R_1 being of size $n_i \Delta \times n_i \Delta$, and R_3 being of size $n_i \times n_i$. Equation (22) simplifies to

$$R_{ee,min} = B_0^* R_3 B_0 \tag{30}$$

It can be shown that, the optimum monic lower-triangular B_0 that minimizes $trace(R_{ee,min})$ is given by the nomic lower-triangular Cholesky factor of R_3^{-1}, i.e.,

10
$$R_3^{-1} = L_3 D_3 L_3^*, \tag{31}$$

which yields

$$B_0^{opt} = L_3, \tag{32}$$

and

$$R_{ee,min} = D_3^{-1}. \tag{33}$$

15   The result is that $\tilde{B}_{opt} = \begin{bmatrix} I_{n_i(\Delta+1)} \\ R_{12}^* R_{11}^{-1} \end{bmatrix} C$, as expressed in equation (21), with the

modified value of R_{11}^{-1}, and with

$$C^* = \begin{bmatrix} 0_{n_i \times n_i \Delta} & B_0^* \end{bmatrix}. \tag{34}$$

A second approach for computing the optimum FIR filter coefficients for the FIG. 1 receiver involves computing a standard – rather than a block – Cholesky

20   factorization of the matrix $R = R_{xx}^{-1} + H^* R_{nn}^{-1} H$ (see the definition following equation (15)) in the form LDL^*. Then, the coefficients of the element 23 filters is given by the n_i adjacent columns of L that correspond to a diagonal matrix with the smallest trace. Therefore, equations (23) and (25) are used to compute the corresponding coefficients, with the understanding that L is now a lower-triangular matrix, rather

25   than a *block* lower-triangular matrix. The equivalence of the two approaches can be shown using the nesting property of Cholesky factorization.

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FIG. 4 presents a flowchart for carrying out the method of determining the filter coefficients that processor 22 computes pursuant to scenario 2. Steps 100 through 120 are the same as in FIG. 3, but the method diverges somewhat in the following steps. In step 131 the partition according to equation (20) is developed for a Δ that minimizes $R_{ee,min}$ of equation (33), and control passes to step 141, where B_0^{opt} is computed based on equations (31) and (32), followed by a computation of $\tilde{B}_{opt}$ based on equations (21) and (34). Following step 141, step 151 computes W_{opt}^* from equation (14), and finally, step 161 installs the coefficients developed in step 141 into the filters of element 26 and the coefficients developed in step 151 into the filters of element 23.
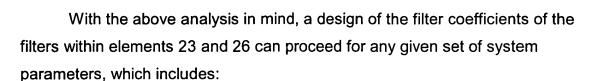
Scenario 3

When multistage detectors are employed, current decisions from all other users, obtained from a previous detection stage, are available to the user of interest. Therefore, suppressing their interfering effects would improve the performance of the receiver. This detection scenario has the same mathematical formulation as scenarios 1 and 2, except that B_0 is now constrained only to be monic, i.e., $e_i^* B_0 e_i = 1$ for all $0 \le i \le n_i - 1$. The general results in equations (21) and (22) still apply with $C^* = \begin{bmatrix} 0_{n_i \times n_i \Delta} & B_0^* \end{bmatrix}$ where B_0 is optimized to minimize $trace(R_{ee,min})$. In short, under scenario 3, the following optimization problem is solved:

$$\min_{B_0} trace(B_0^* R_3 B_0) \text{ subject to } e_i^* B_0 e_i = 1 \text{ for all } 0 \le i \le n_i - 1, \quad (33)$$

where R_3 is as defined in equation (29). Using Lagranage multiplier techniques, it can be shown that the optimum monic B_0 and the corresponding MMSE are given by

$$B_0^{opt} = \frac{R_3^{-1} e_{i-1}}{e_i^* R_3^{-1} e_i}; \quad 0 \le i \le n_i - 1. \quad (34)$$

Thus, the method of determining the filter coefficients that processor 22 computes pursuant to scenario 3 is the same as the method depicted in FIG. 4, except that the computation of B_0^{opt} within step 141 follows the dictates of equation (34).

With the above analysis in mind, a design of the filter coefficients of the filters within elements 23 and 26 can proceed for any given set of system parameters, which includes:

- MIMO channel memory between the input points and the output point of the actual transmission channel, v,
- The number of pre-filter taps chosen, N_f,
- The shortened MIMO memory, N_b,
- The number of inputs to the transmission channel, n_i,
- The number of output derived from the transmission channel, n_o,
- The autocorrelation matrix of the inputs, $\mathbf{R}_{xx}$,
- The autocorrelation matrix of the noise, $\mathbf{R}_{nn}$,
- The oversampling used, l, and
- The decision delay, Δ.

It should be understood that a number of aspects of the above disclosure are merely illustrative, and that persons skilled in the art may make various modifications that, nevertheless, are within the spirit and scope of this invention.

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